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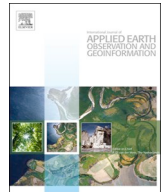
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Spatio-temporal divergence in the responses of Finland's boreal forests to climate variables

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ABSTRACT

Spring greening in boreal forest ecosystems has been widely linked to increasing temperature, but few studies have attempted to unravel the relative effects of climate variables such as maximum temperature (TMX), minimum temperature (TMN), mean temperature (TMP), precipitation (PRE) and radiation (RAD) on vegetation growth at different stages of growing season. However, clarifying these effects is fundamental to better understand the relationship between vegetation and climate change. This study investigated spatio-temporal divergence in the responses of Finland's boreal forests to climate variables using the plant phenology index (PPI) calculated based on the latest Collection V006 MODIS BRDF-corrected surface reflectance products (MCD43C4) from 2002 to 2018, and identified the dominant climate variables controlling vegetation change during the growing season (May–September) on a monthly basis. Partial least squares (PLS) regression was used to quantify the response of PPI to climate variables and distinguish the separate impacts of different variables. The study results show the dominant effects of temperature on the PPI in May and June, with TMX, TMN and TMP being the most important explanatory variables for the variation of PPI depending on the location, respectively. Meanwhile, drought had an unexpectedly positive impact on vegetation in few areas. More than 50 % of the variation of PPI could be explained by climate variables for 68.5 % of the entire forest area in May and 87.7 % in June, respectively. During July to September, the PPI variance explained by climate and corresponding spatial extent rapidly decreased. Nevertheless, the RAD was found to be the most important explanatory variable to July PPI in some areas. In contrast, the PPI in August and September was insensitive to climate in almost all of the regions studied. Our study gives useful insights on quantifying and identifying the relative importance of climate variables to boreal forest, which can be used to predict the possible response of forest under future warming.

1. Introduction

The boreal forest, one of the largest terrestrial biomes on Earth, has attracted great attention as the northern high latitudes are experiencing more rapid warming than other regions and boreal forests are expected to be particularly sensitive to climate warming (Franke et al., 2019; Gauthier et al., 2015). Many studies have investigated changes related to global warming in boreal forests, at both a regional and continental scale, e.g., in Alaska (Beck et al., 2011; Parent and Verbyla, 2010), Canada (D'Orangeville et al., 2016; Goetz et al., 2005; Peng et al., 2011) and Eurasia's boreal forest (Buermann et al., 2014; Hellmann

et al., 2016). In contrast to Canadian and Russian boreal forests, Scandinavian boreal forests, especially the boreal forests of Finland, have high intensity forest management, which may reduce forest resilience and increase risks associated with climate change (Gauthier et al., 2015). Understanding the variability of these forests and their responses to climate change is therefore crucial for assessing current management practices and promoting further adaptation to climate change.

Some studies have examined the effects of climate change on forests in Finland using ecosystem models (Garcia-Gonzalo et al., 2007; Kellomäki et al., 2008; Talkkari and Hypén, 1996), and investigated

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variations in plant phenology, growth patterns and albedo of the Finnish forests using remote sensing (Jin et al., 2017; Karlsen et al., 2009; Lukeš et al., 2016; Manninen et al., 2019; Ulsig et al., 2017). However, the response of Finnish forests to ongoing climate change on a regional scale have received relatively less attention. In recent decades, especially since 2003, summer heat wave events (HW) in Europe have increased and caused massively negative impacts on European ecosystems due to HW most likely resulting in drought and wildfires (Rebetez et al., 2009; Sutanto et al., 2020; Zhang et al., 2020). Although forest can be more resilient than other land cover types (e.g. grassland) during HW (Teuling et al., 2010), it is not clear how the forest resilience will vary as future warming could accelerate. Hence, it is vital to understand to what extent the response of forest to climate change could be predicted.

The climate of the boreal forests generally exhibits strong seasonal variation with a short and moderately warm summer and long and cold winter. The key factor in vegetation growth is generally thought to be the temperature at high northern latitudes (Nemani et al., 2003; Seddon et al., 2016). Temperature seasonality over northern lands has been weakening over the past decades due to climate warming (Xu et al., 2013). Increasing temperature may alter the response of vegetation to other climate variables (e.g., precipitation, radiation). For example, the absence of summer precipitation associated with warmer temperature has exerted a negative impact on vegetation greenness in boreal forests in western central Eurasian since the mid-1990s (Buermann et al., 2014). Overall, we still lack a comprehensive understanding of the responses of vegetation to different climate variables.

The normalised difference vegetation index (NDVI), defined as the ratio of red and near infrared (NIR) bands, has been most widely used to monitor large-scale vegetation activity. However, NDVI is less reliable for assessing forest changes in boreal regions due to influences of snow cover and saturation effects (Beck et al., 2006; Sellers, 1985; Stenberg et al., 2004). To overcome the influences of snow, signal saturation and low sun elevation angles in boreal ecosystems, Jin and Eklundh (2014) proposed a physically based vegetation index, the plant phenology index (PPI). The index has been proven to be a better surrogate of vegetation activity than NDVI and the Enhanced Vegetation Index (EVI) at northern Europe (Karkauskaite et al., 2017) and have good consistency with leaf area index (LAI) and gross primary productivity (GPP) (Abdi et al., 2019; Jin et al., 2017).

In the present study, we employed PPI as a proxy for vegetation activity to explore spatio-temporal divergence in the responses of Finland's boreal forests to climate variables and confirm the dominant climate variables affecting forest on a monthly scale. The partial least squares (PLS) regression method, which combines the strength of principal component analysis (PCA) and multiple linear regression, was used to quantify the fraction of PPI variance explained by climate variables and separate the relative importance of these variables, by maximally explaining the covariance between vegetation and climate variables.

2. Data and methods

2.1. Study area

Finland is the most forested country in Europe. Approximately 75 % of Finland's land area is covered by forests. In order to exclude non-forest areas in our study, we used the 300 m global land cover (LC) dataset from the European Space Agency (ESA) (<https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-land-cover?tab=overview>). This dataset describes global land surface into 22 classes defined by the United Nations Food and Agriculture Organization's (UN FAO) Land Cover Classification System (LCCS). We selected 'Tree cover' classes in the dataset to extract forest area. To minimize the effects of land cover change on vegetation, we only analysed the forest pixels with unchanged LC type over the study period. Fig. 1 shows the spatial

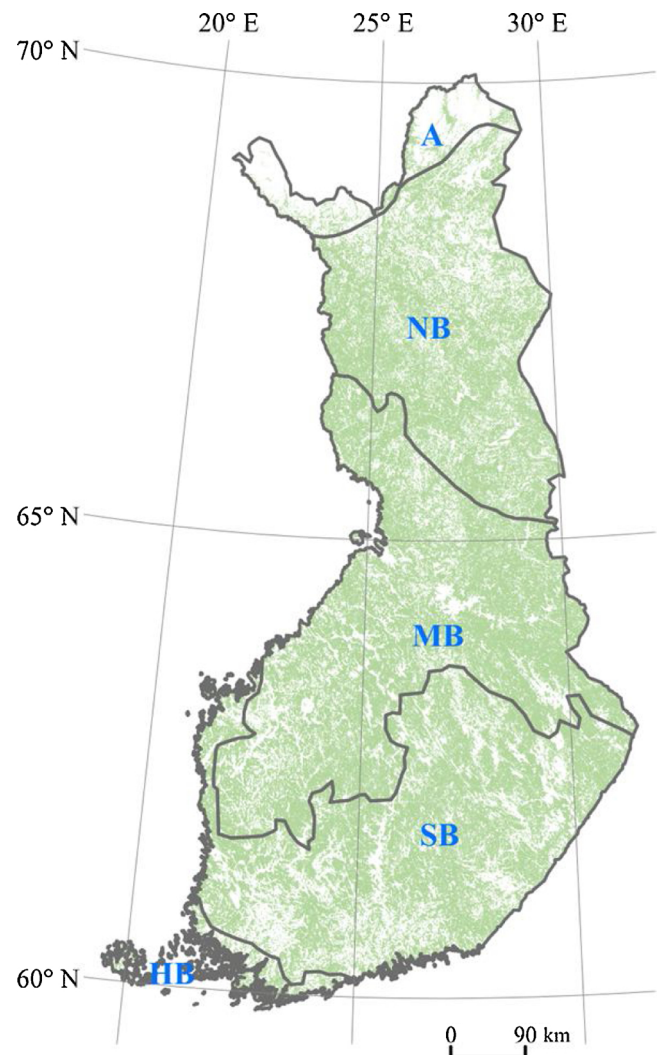


Fig. 1. Spatial distributions of forest areas (green color) derived from the ESA land cover products, and five vegetation zones in Finland: the hemi-boreal (HB), southern boreal (SB), middle boreal (MB), northern boreal (NB) and Alpine (A) zones. The vegetation zones (HB, SB, MB and NB) were vectorized according to Härmä et al. (2009), and the boundary of the A zone was derived from <https://www.eea.europa.eu/data-and-maps/data/biogeographical-regions-europe-3/> (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

distribution of unchanged forest pixels derived from the 300 m LC products between 2002 and 2018.

According to the phytogeographical classifications of Ahti et al. (1968), Härmä et al. (2009) and the European Environment Agency (2016), Finland can be divided into five vegetation zones from south to north: the hemi-boreal (HB), southern boreal (SB), middle boreal (MB), northern boreal (NB) and Alpine zones (A) (Fig. 1). The first four boreal zones are dominated by coniferous forests, mainly consisting of Scots pine (*Pinus sylvestris*) and Norway spruce (*Picea abies*), and most of the forests have a higher percentage of Scots pine than Norway spruce in the four boreal zones, except in some areas of the southern boreal zone (Brus et al., 2012). The Alpine zone located in northern Finnish Lapland is dominated by shrubs and mountain birch (Franke et al., 2019). Although there are some differences in forest phenology for different vegetation zones of Finland, the growing-season months generally range from May to September for most areas of Finland (Böttcher et al., 2016; Jin et al., 2017; Lukeš et al., 2016; Manninen et al., 2019). The following monthly analysis was restricted to May to September.

2.2. Data

2.2.1. Vegetation data

The daily MODIS Nadir BRDF-Adjusted Reflectance (NBAR) products from MCD43C4 Collection 6 (Wang et al., 2018) at a 0.05° spatial resolution were used to calculate the PPI according to the method described by Jin and Eklundh (2014). The MCD43 products have been produced by using data from both the Terra and Aqua satellites. Since Aqua data is only available after May 2002, our analysis used the period of 2002 to 2018. The surface reflectance data from MCD43C4 NBAR products were first filtered for snow (snow flag set to 0) and relative good quality retrievals (BRDF flag set to 0, 1 and 2) according to Walther et al. (2019). The PPI were then calculated and averaged to the monthly values at the original 0.05° resolution.

Since NDVI has been widely used to monitor vegetation activity, we here compared the performance of NDVI and PPI in Finland's boreal forests. We selected the widely-used bi-monthly Global Inventory Monitoring and Modelling System (GIMMS) NDVI 3g.v1 dataset with a spatial resolution of 1/12° (<https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/>) for the comparison during the overlapping period 2002–2015. To ensure the quality of GIMMS NDVI data, pixels flagged as possible snow/cloud (flag 2) were excluded. The NDVI data with quality flags of 0 ('good value') and 1 ('NDVI retrieved from spline') were kept. In addition, considering that all pixels containing snow were removed when calculating the PPI based on MCD43C4 products, and the NDVI pixels on the corresponding locations were also excluded from the correlation analysis between PPI and NDVI, the remaining pixels can therefore be supposed less affected by snow. We calculated monthly NDVI by averaging the bi-monthly values to match the monthly PPI. The PPI data were resampled from the original 0.05° to 1/12° resolution to match the NDVI data. To identify forest regions for the comparison, unchanged forest pixels were derived from the 300 m ESA LC products between 2002 and 2015 and then aggregated to a 1/12° pixel scale where the majority of the 300 m pixels have the same land cover type 'Tree cover'.

We found that there was no significant correlation between NDVI and PPI for many areas of Finland (Fig. S1). Then, we chose forest inventory data from the Multi-Source National Forest Inventory of Finland (MS-NFI) products in 2013 (Mäkisara et al., 2016) as a representative year to evaluate the performance of NDVI and PPI in capturing actual forest growth. The MS-NFI products were made using field data, satellite images, digital map data and related georeferenced data based on the improved k-NN (k-Nearest Neighbour) method (Mäkisara et al., 2016). Three variables were selected from the MS-NFI products: the growing stock, canopy cover and stand basal area.

The proxies of vegetation productivity based on the PPI/NDVI integrated from May to September showed relatively stronger relationships with these three forest inventory variables than the maximum PPI/NDVI during May to September (Figs. S2 and S3). Meanwhile, the relationships between PPI and forest inventory variables were always stronger than those between NDVI and forest inventory variables. The highest correlations occurred between the integrated PPI and canopy cover. Hence, PPI as a proxy of vegetation was more suitable than NDVI, and GIMMS NDVI should be used with caution at least in this study area. In the following analysis the PPI data were projected to the ETRS-TM35FIN coordinate system and resampled to 10 km spatial resolution using the Python package GDAL to match the climate data.

2.2.2. Climate data

Climate variables used in this study included maximum, minimum and mean air temperatures (TMX, TMN and TMP), precipitation (PRE), radiation (RAD), and drought represented by the standardised precipitation-evapotranspiration Index (SPEI). These climate variables, except for SPEI, were extracted from the gridded daily climatology dataset of Finland (FMI ClimGrid) (Aalto et al., 2016). The dataset has good quality control standards and covers the period from 1961 to

2018, with a spatial resolution of 10 km over the ETRS-TM35FIN coordinate system. The daily climate data were aggregated to monthly climate averages (for TMN, TMX, TMP and RAD) and monthly totals (for PRE). For SPEI, we used the 1-month SPEI to represent drought based on a 1-month time scale. Lower SPEI values indicate drier conditions. The calculation of SPEI requires potential evapotranspiration (PET) and precipitation data (Vicente-Serrano et al., 2010). Because PET is not made by the FMI ClimGrid project, we used the monthly Penman-Monteith PET time series from CRU TS v. 4.03 at 0.5° resolution (Harris et al., 2020) and resampled it to a spatial resolution of 10 km to match the FMI ClimGrid. Then, we calculated the SPEI from the PET data and the abovementioned PRE data using the R package SPEI (version 1.7).

2.3. Statistical analysis

2.3.1. Trend analysis

The Mann-Kendall (MK) trend test was used to examine the presence of a monotonic trend in the PPI time series. This approach is a robust nonparametric rank-based method and does not require the data series to follow any particular distribution (Kendall, 1955; Mann, 1945). The magnitude of the PPI trends was calculated using the Theil-Sen slope estimator, a robust nonparametric slope estimator (Sen, 1968). It estimates the slope of a time series as the median slope between all data pairs of observations and its major advantage is its resistance to the presence of outliers (Gocic and Trajkovic, 2013). We used the Python package *pymannkendall* (version 1.2) (Hussain and Mahmud, 2019) to perform the Mann-Kendall trend test and return the Sen's slope based on a 5 % significance level.

2.3.2. Partial least squares regression

The response of PPI to climate variables was evaluated using the partial least squares (PLS) regression method. Potential lagged effects of climate on PPI were also considered when performing PLS regression. In the fitted PLS regression model, the dependent variable was PPI and explanatory variables included 18 variables: TMP, TMX, TMN, SPEI, PRE, RAD and their corresponding lagged variables which were assumed to have potential time-lag effects of 1–2 months on PPI. The PLS regression method is a robust multivariate technique that combines features of principal component analysis and multiple regression (Abdi, 2010) and is more parsimonious and statistically robust than principal components regression (Smoliak et al., 2015). Moreover, PLS regression can effectively deal with the problem of multicollinearity that occurs whenever an independent variable is highly linearly correlated with one or more other independent variables. Multicollinearity can result in overfitting in general multiple regression models. So, PLS regression is particularly suitable for our case because the selected climate variables in our study are to some extent interrelated. Although PLS regression was first applied in the social sciences and is now most widely used in chemometrics and related fields, its utility in geosciences has been demonstrated by many studies (Black et al., 2017; Ceglar et al., 2016; Guo et al., 2017; Hansen and Schjoerring, 2003; Matthes et al., 2015; Prasad et al., 2008; Smoliak et al., 2010).

The PLS regression method is based on linear combinations (called latent vectors or PLS components) of a set of independent variables that maximise the variance explained in one or more dependent variables (Smoliak et al., 2010). A significant number of PLS components is determined by cross-validated R^2 values (Jong et al., 2001). The cross-validated R^2 , indicating the square of the correlation between the actual and predicted values, is often called Q^2 in PLS regression analysis. A PLS component can be kept if its Q^2 value is greater than or equal to 0.0975 (Abdi, 2010). If the Q^2 is less than 0.0975 for the first PLS component, the PLS regression model is not statistically significant. The percentage of variance of dependent variable (Y) explained by the PLS components is called R^2Y (Brunelli et al., 2009).

In addition, PLS regression also provides an estimate of the

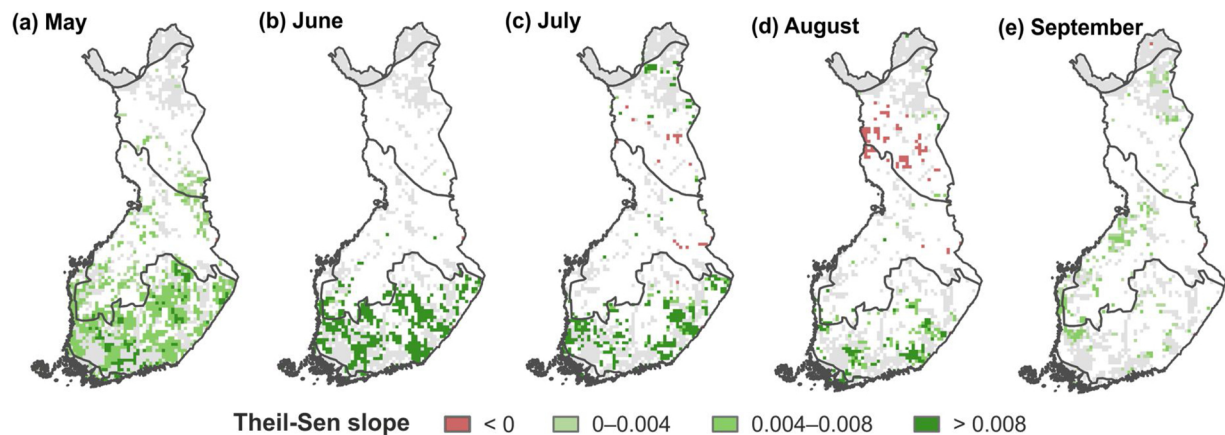


Fig. 2. Spatial distribution of PPI trends based on Theil-Sen slope trend analysis for May, June, July, August and September from 2002 to 2018. Areas with non-significant trends ($p > 0.05$ following Mann-Kendall test) are shown in white, and non-forest areas are masked in grey.

importance of each independent variable, called the variable importance in projection (VIP) score (called PLS-VIP method). The VIP score represents the statistical contribution of each independent variable to the overall fitted PLS regression model across all latent vectors (Matthes et al., 2015). Higher VIP score for an independent variable means higher importance for explaining the variance of dependent variable(s), and independent variables with a VIP score greater than 1 are considered significant. The details of the VIP score can be found in Chong and Jun (2005). Next, PLS regression analysis was performed pixel by pixel for different months using the R package *mixOmics* (version 6.10.9) (Rohart et al., 2017) in the R (version 3.6.3) statistical environment.

3. Results

3.1. Trends in monthly PPI

Fig. 2 shows the spatial patterns of monthly PPI trends from 2002 to 2018 and the corresponding magnitude of the PPI trends. It is clear that the PPI trends were not uniform across the vegetation zones for different months. Significant PPI increase mainly occurred in some areas of the SB zone in May, June and July. Although the percentages of pixels with significant positive trends in the zone in June (43.9 %) and July (29.6 %) were smaller than that in May (69.6 %), the higher PPI rise occurred in June and July. However, overall the number of pixels with no significant PPI trends was far greater than those with significant trends.

3.2. Variation of PPI explained by climate variables

In order to understand the relationship between PPI and climate variables, the PLS regression was used to quantify the fraction of the PPI variation explained by climate variables on a pixel-by-pixel basis. The following 18 climate variables, TMP, TMX, TMN, PRE, RAD, SPEI and their corresponding lagged variables at lag -2 to -1 months (i.e., climate leading PPI 1–2 months), were considered as predictor variables in PLS regression models.

As illustrated in Fig. 3, the percentages of pixels (dark green pixels) successfully fitted by PLS regression models were very high during the start and rapid growth stage of vegetation, with 81.5 % (May) and 94.1 % (June) of the entire forest area. Meanwhile, the fraction of PPI variation explained by climate variables was also relatively high. Over 50 % of the variation could be explained for 68.5 % of the entire forest area in May and 87.7 % in June, respectively. However, the percentages of pixels with PPI variation explained by climate variables dramatically decreased in July (30.1 %), August (21.6 %) and September (3.4 %).

Spatially, the impact of climate on PPI showed a plausible

south–north gradient from May to June, which was characterised by: 1) in May, the areas where PPI variance could be explained by climate variables mainly occurred in the SB and MB zones (Fig. 3a); and 2) in June, it is clear that these areas extended northward, with high fraction of PPI variance explained by climate in the NB zone (Fig. 3b). In July, there was no significant relationship between PPI and climate in southern Finland, and the significant relationship only occurred in the NB and MB zones with smaller spatial extent than in May and June. In August and September, by comparison, no regular pattern of PPI–climate relationship was found. There was essentially no relationship between PPI and climate variables across all vegetation zones, especially in September.

3.3. Contribution of climate variables to PPI variance

Using the PLS-VIP method, VIP scores were calculated to interpret the contribution of each climate variable to PPI variance. For a given pixel, each independent variable got a unique VIP score. Since the independent variables included 18 climate variables, the VIP scores ($VIP > 1$) could be divided into 18 ranks in descending order. This means that, for a given pixel, the VIP score of the independent variable in the 1st VIP score rank is larger than that in the 2nd VIP score rank, and so on. The independent variable in the 1st VIP score rank was hence called the most important variable.

To clearly show the relative importance of each climate variable, we further summarised the number of pixels explained by each climate variable and sorted them according to the VIP score ranks for each month (Fig. 4). The VIP score ranks at lower level (10th–18th) were not shown because the number of pixels in these ranks was too few. It can be clearly seen that in May (Fig. 4a) the number of pixels corresponding to TMP was the largest in the 1st VIP score rank, followed by TMX, and the number of pixels corresponding to other climate variables decreased quickly. In June (Fig. 4b), there was an obvious time-lag effect that May TMP (also followed by May TMX) was the most important explanatory variable in both the 1st VIP and the 2nd VIP score ranks. In July (Fig. 4c), RAD became the most important explanatory variable despite relatively few in the number of pixels. In August and September (Fig. 4d and e), corresponding to Fig. 3d and e, the number of pixels explained by climate variables decreased quickly and the time-lag effect almost disappeared; nevertheless, it is worth noting that in August the number of pixels explained by TMN was relatively larger than by other climate variables.

Fig. 5 shows the spatial distribution of the major climate variables in the 1st VIP score rank and their corresponding standardised regression coefficients for different months, except for September due to very low number of pixels. In May, TMP was mainly distributed in middle and southern areas, and TMX mainly occurred in western and northern

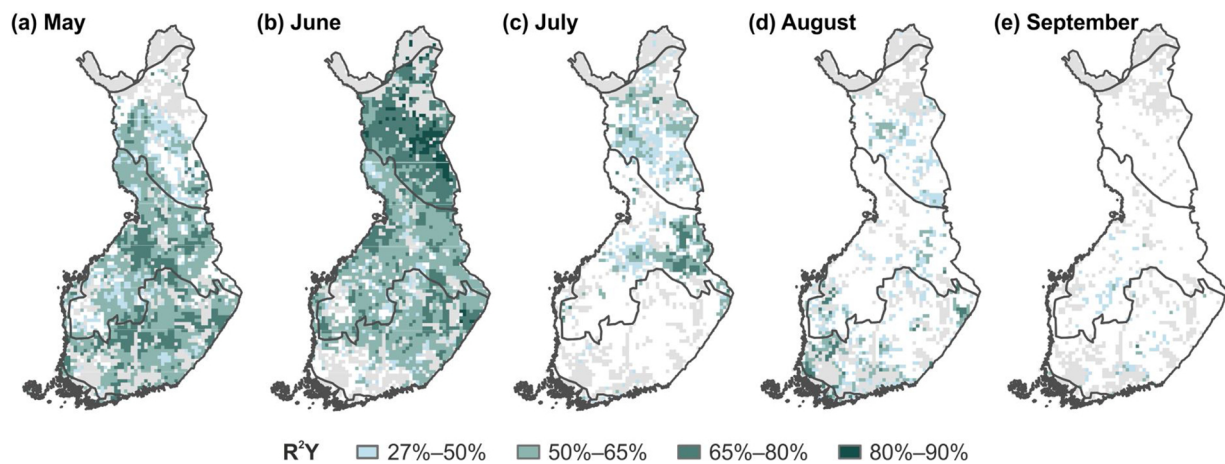


Fig. 3. Spatial patterns of the fraction of PPI variance explained by climate variables based on partial least-squares (PLS) regression for May (a), June (b), July (c), August (d), and September (e). Areas where the PLS regression relationship between PPI and climate variables was not significant are shown in white, and non-forest areas are masked in grey.

areas (Fig. 5a). In June, although the distribution patterns of the climate variables were less clear than in May, it can be found that the May TMX was still dominant in northern areas (Fig. 5b). Meanwhile, the minimum temperature, including TMN and TMN_Lag (-1), occurred in southern areas. In July, the spatial distribution of the most important variables became more irregular, and these variables were only found in some local areas of the MB and NB zones (Fig. 5c). As regards the regression coefficients, the temperature had the positive impacts on PPI in most areas (Fig. 5e and g), which is not surprising. However, in August, there was an unexpected pattern that TMN as the most important variable had negative relationships with PPI in southwestern parts of the SB zone (Fig. 5d). In addition, although SPEI only occurred in small, dispersed local areas (Fig. 5a and c), it corresponded to unexpectedly negative regression coefficients in May (Fig. 5e) and July (Fig. 5g), which means that drought exerted positive impacts on PPI.

4. Discussion

4.1. High fraction of the variation of PPI explained by climate in May and June

Overall the areas with significant increases in PPI were much less than those with no significant trends from 2002 to 2018 in Finland's forest (Fig. 2). Significant increases in PPI only occurred in some parts of the SB zone in May and June. By contrast, there were large spatial extents with high percentages of the variation of PPI explained by climate in May and June, besides those areas with significant increase in PPI (Fig. 2a and b). As expected, temperature was found to be the most important explanatory variable to PPI. Previous studies (Chen et al., 2018; Menzel et al., 2006; Wang et al., 2011) have indicated that temperature controlled vegetation growth in most areas of the Northern

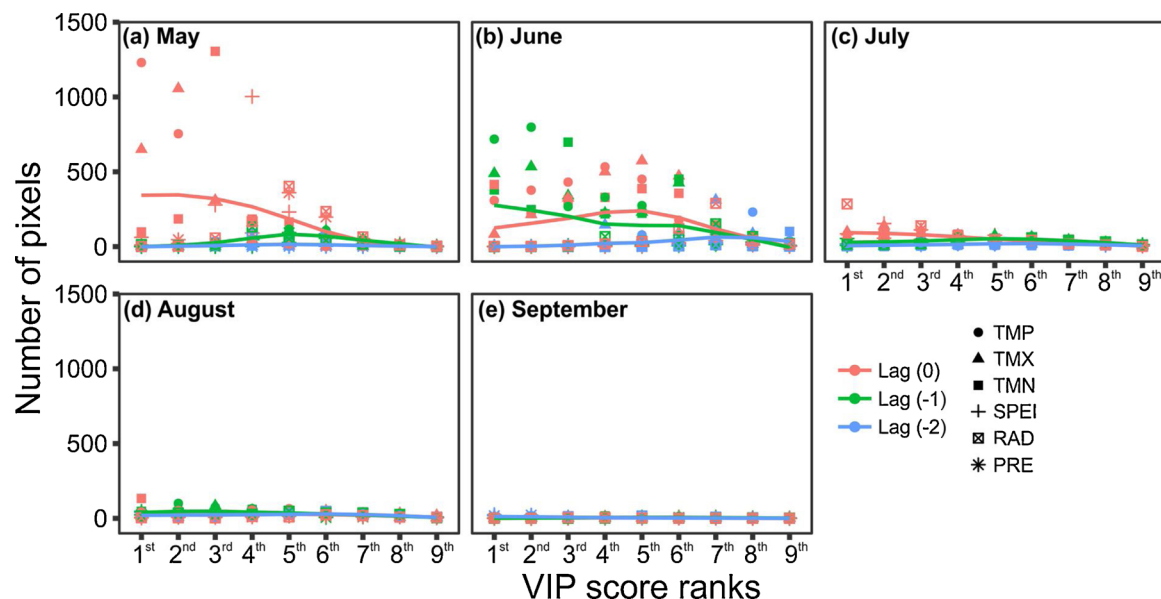


Fig. 4. Number of pixels explained by each climate variable according to the ranks of the variable importance in projection (VIP) scores for May (a), June (b), July (c), August (d) and September (e). For a given pixel, the climate variable in the 1st VIP score rank is the most important for explaining the PPI variance, and so on. Colors represent different time lags of -2 to 0 months which means that the climate variables were shifted one month (Lag (-1)) and two months (Lag (-2)) prior to the PPI, and 'Lag (0)' indicates the concurrent relationship between PPI and climate variables. The symbols represent the different climate variables.

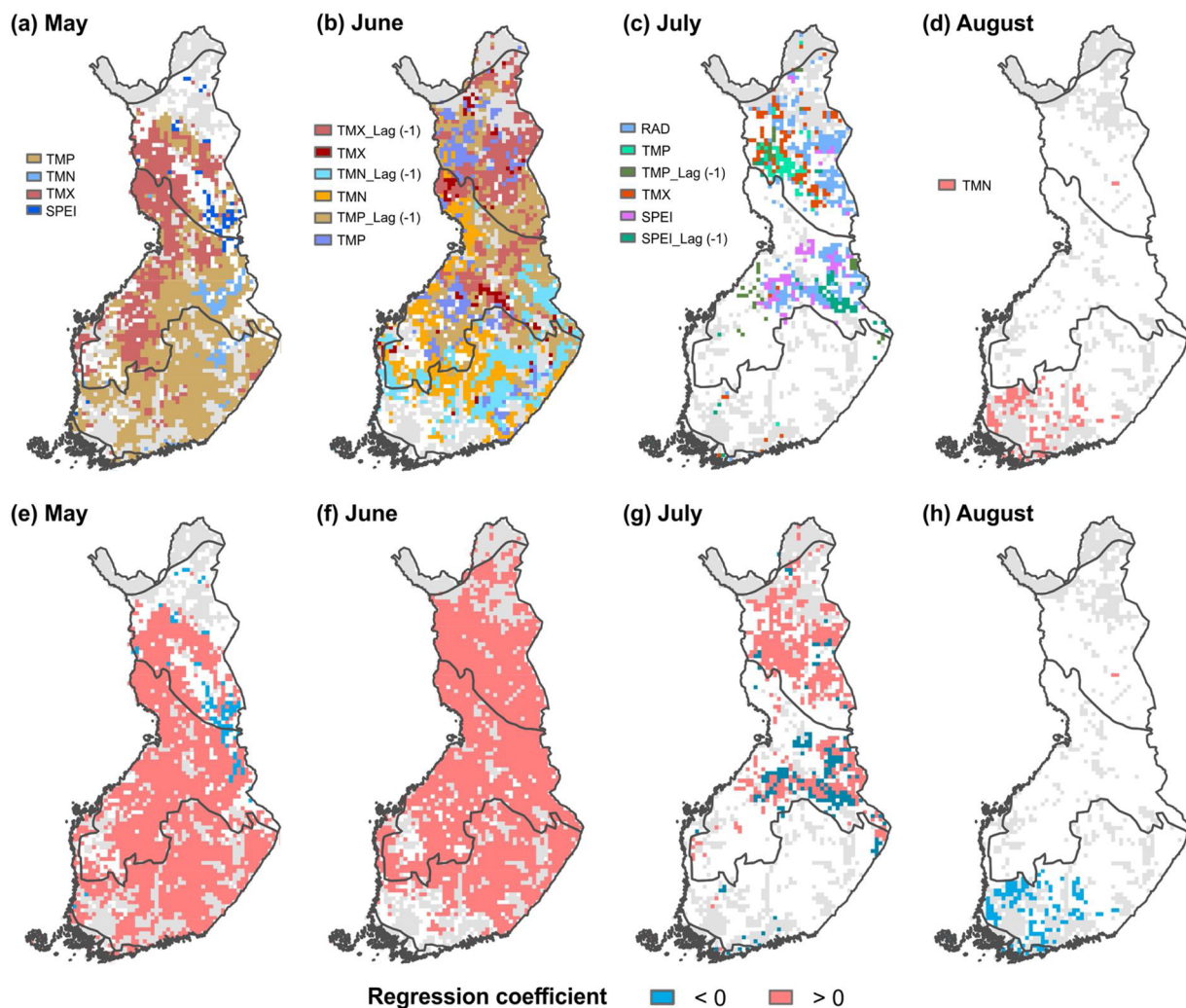


Fig. 5. Spatial distributions of the major climate variables in the 1st VIP score rank (top) and their corresponding standardised regression coefficients (bottom) in May (a), June (b), July (c) and August (d). The white colour denotes areas where the PLS regression model was not significant. Non-forest areas are masked in grey.

Hemisphere (NH) during spring.

Although the enhanced vegetation productivity has been linked to the warmer spring temperature since the 1980s in the NH (Schwartz et al., 2006; Wang et al., 2011), one recent study (Wang et al., 2019) noted that there was no significant trend in spring and autumn phenology during the global warming hiatus between 1998 and 2012, which is basically agreement with our findings on the PPI with no significant changes in more areas during the period of 2002–2018 (Fig. 2). We examined monthly temperature (TMX, TMN, TMP) trends in Finland during May to September from 2002 to 2018 and found no significant trends (not shown), which could explain why the PPI in many areas had no significant change despite the strong relationship between PPI and temperature in May and June. In addition, some studies (Wen et al., 2019; Wu et al., 2015) using GIMMS NDVI showed that most vegetation did not exhibit time-lag effects related to temperature at the high latitudes in the NH. Our results show an exceptional time lag effect that June PPI was related to May temperature (Fig. 4b and 5b), suggesting that the temperature during the start of vegetation growth played the most important role with a lasting impact of two months.

Spatially, the areas with high percentages of the variation of PPI explained by climate showed a plausible south–north gradient from May to June (Fig. 3a and b). Meanwhile, the most important climate variables also changed along the south–north gradient, with the most important variables being TMX in northern Finland during May and

June, TMP in southern Finland during May, and TMN in southern Finland during June, respectively (Fig. 5a and b). The key for understanding the south–north gradient is that the phytogeographical character in Finland essentially follow the main south–north climate gradient (Helmens, 2009). In other words, climate is the main driver of the vegetation zones in Finland and thus could result in the above-mentioned south–north gradient in explaining the responses of PPI to climate. Similarly, Solantie (2005) indicated the importance of vegetation zones in determining the productivity of Finnish boreal forests. Several recent studies (Beck et al., 2011; Berner et al., 2013; Sherriff et al., 2017) also found that the responses of vegetation growth and productivity to climate warming varied along biogeographic gradients in Alaska and Siberia.

Although temperature explained the majority of PPI variation in May and June, the importance of other variables should not be ignored. For example, in May, there were few areas where SPEI was the most important explanatory variable with unexpectedly negative regression coefficients (Fig. 5a and e), suggesting that drought exerted a positive impact on PPI at local scale. The positive influence of drought could be related to the ability of the forest to access soil water, depending on local microsite conditions. Nicolai-Shaw et al. (2017) found that forests exhibit a much weaker response to drought than other land cover types due to the ability of trees to utilise water in deeper soil layers. The positive effect of drought on vegetation growth has been observed in some relatively humid regions, such as China's subtropical pine forests

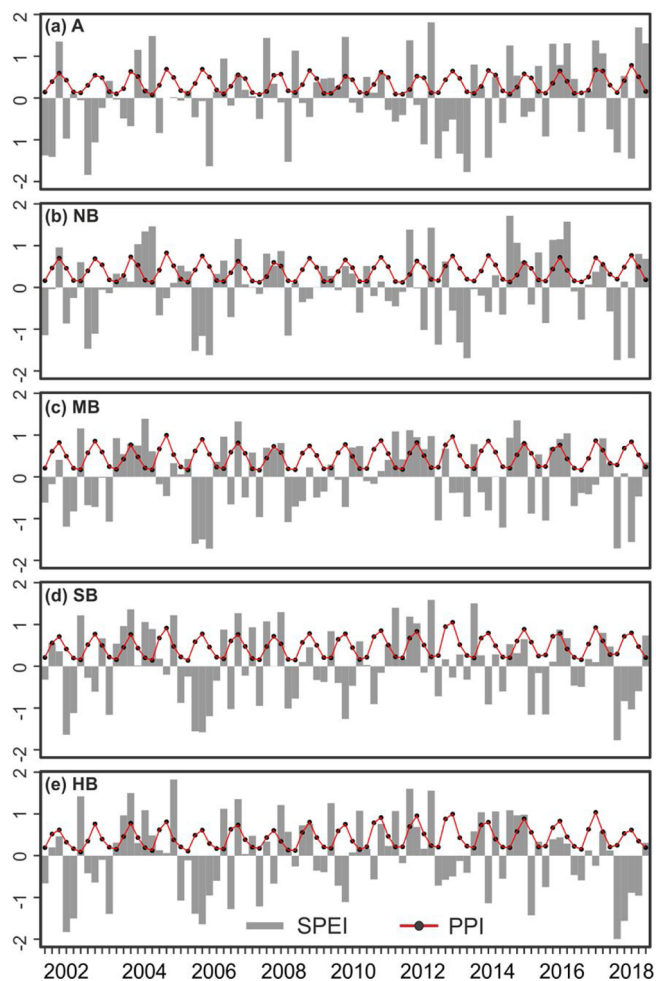


Fig. 6. Multiyear time series of the region averaged monthly SPEI and PPI during May to September from 2002 to 2018.

(Huang et al., 2018). To the best of our knowledge, the present study is the first to highlight the positive role of drought in boreal forest growth, although this depends on the location and time.

It can be seen from Fig. 6 that the regionally averaged SPEI was capable of adequately capturing meteorological drought events (e.g., droughts of 2002–2003, 2006 and 2018). In particular, there was the lowest SPEI values in 2018 in all zones except the northernmost A zone (Fig. 6), which is in accordance with an actual, exceptionally dry thermal growing season in Finland in 2018 (Lehtonen and Pirinen, 2019; Liu et al., 2020). In contrast, the PPI basically had no obvious fluctuation across the period of 2002–2018. Even during the severe droughts of 2006 and 2018, the decline of PPI only occurred in the HB zone, which could be attributed to severe precipitation deficit, periodic low groundwater levels and shallow soil profiles in the area (Lehtonen and Pirinen, 2019; Muukkonen et al., 2015). The southwestern Finland is more vulnerable to drought damage than the other parts of Finland, but the actual occurrences of drought damage to forests have somewhat low probabilities in Finland. Even during the summer of 2006, with its extremely dry conditions, less than 30 % of the forest observational sites showed drought-damage symptoms in southern Finland (Gao et al., 2016).

4.2. Large unexplained variation of PPI during July to September

As shown in Fig. 3, although the response of PPI to climate was very evident in May and June, the unexplained variability of PPI since July was far larger than that explained. Moreover, unlike in May and June,

RAD not temperature became the most important explanatory variable to July PPI for relatively more pixels (Figs. 4c and 5 c), which is in agreement with the finding of the important impacts of solar radiation on vegetation at high northern latitudes during summer (Kong et al., 2017). Similarly, Chen et al. (2018) found that the influence of temperature on vegetation decreased from spring to summer, and the impact of PRE gradually increased in many areas of the NH. Our results confirmed that the importance of TMP weakened in July but the influence of PRE was not found. This is probably because water is generally not the key factor limiting vegetation growth in many areas of Finland due to relatively low evapotranspiration and moderate precipitation (Veijalainen et al., 2019), which is also supported by the generally weak relationships between SPEI and PPI (Fig. 6). Vegetation growth tends to be controlled by water availability for mid latitude semi-arid regions not high latitudes (Jung et al., 2017; Liu et al., 2020).

Considering that there are three major climate variables that drive vegetation growth: temperature, precipitation and solar radiation (Nemani et al., 2003; Seddon et al., 2016), RAD was the most important explanatory variable to July PPI, meaning that both temperature and precipitation were sufficient in these areas in July—the warmest month in Finland. So, given that temperature, water availability and radiation could not be the limiting factors in July, it would be easily understood about the decreasing explanatory power of climate variables. It suggests that non-climate factors may control the variation of July PPI in more areas, particularly in southern Finland.

The responses of PPI to climate in August and September became more complicated as there was almost no significant relationship between PPI and climate variables. Meanwhile, it was unexpected that there was a negative relationship between minimum temperature and PPI in few areas of southwestern Finland. The local negative relationship is hard to interpret. In southwestern Finland, the forests typically have tall stands with relatively high minimum temperature during the growing season, and their productivity was positively associated with minimum temperatures (Solantie, 2005). In view of these, we suspected that the vegetation activity in August and September might not be adequately captured by PPI. This may be due to some limitations that PPI is very sensitive to noise during peak growing season and tends to have large fluctuations at high LAI level (Jin and Eklundh, 2014). High values and relatively slow changes in LAI from July to August and even September in Finnish coniferous forest (Rautiainen et al., 2012) could lead to unstable relationships between PPI and actual vegetation activity, and partially contribute to the limited explanatory power for PPI responses to climate in these months. Another possible reason for the low explanatory power is the more complicated effect of climate on phenology in autumn than in spring (Jiang et al., 2020). For example, Richardson et al. (2010) found that vegetation productivity and phenological anomalies had weak relationships with climate drivers in late-season (July–December) compared with early-season (January–June).

As climate is only one aspect of environment change, we suggest that future vegetation-related studies should assess the contributions of many other non-climate variables, especially when climate is not a limiting factor at certain stage of plant growth. It would lead to a more comprehensive understanding of the key mechanisms driving vegetation change. In addition, high forest management intensity across Finland (Gauthier et al., 2015) may affect the response of vegetation to climate and thereby, to some degree, bring down the explanatory power of climate on vegetation (Kellomäki et al., 2008). However, the forest management practices usually occur at smaller spatial scales in Finland, which means that it may be difficult to estimate the effects of human influences on the vegetation from coarse resolution satellite data (Lukeš et al., 2016). High spatial resolution data (e.g. Landsat, Sentinel-2) has the potential to provide accurate information about vegetation at fine scale, though their performance may be limited by low temporal resolution and high cloud cover in Finland.

5. Conclusions

This study examined the spatio-temporal characteristics of vegetation change using monthly PPI during May to September from 2002 to 2018 and identified critical climate variables affecting PPI in Finnish boreal forests. There were generally no significant trends in PPI in many areas, except in some parts of the SB zone. The relationship between PPI and climate variables varied depending on the location and months. The PPI variance explained by climate variables was generally greater than 50 % with large spatial extents in May and June. The VIP values showed that temperature was the most important climate variable for explaining the variation of PPI in May and June. We also found a time lag of one month that May temperature had a major impact on June PPI. Drought exerted a positive impact on forest in small local areas, which could depend on the availability of soil water and the ability of the forest to access soil water. The PPI variance explained by climate variables rapidly decreased during July to September. Nevertheless, radiation was found to be the most important explanatory variable for July PPI in a few areas. The variation of July PPI in more areas might be attributed to local environment conditions. Our results emphasize the importance of temperature on Finland's forests during May to June and quantify the responses of PPI to climate variables.

CRedit authorship contribution statement

Meiting Hou: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Visualization, Funding acquisition. **Ari K. Venäläinen:** Conceptualization, Methodology, Resources, Investigation, Writing - review & editing, Supervision. **Linping Wang:** Methodology, Software, Visualization. **Pentti Pirinen:** Resources, Data curation. **Yao Gao:** Methodology, Resources. **Shaofei Jin:** Software, Investigation. **Yuxiang Zhu:** Investigation, Funding acquisition. **Fuying Qin:** Resources, Writing - review & editing. **Yonghong Hu:** Resources, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.jag.2020.102186>.

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